

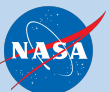
CERES Cloud Radiative Swath (CRS) Validation & Improvements to FLASHFlux via Machine Learning

Ryan Scott, Fred Rose, David Rutan

Science Systems & Applications, Inc.

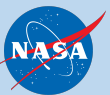
Paul Stackhouse, Seiji Kato, David Doelling,
Norman Loeb

NASA Langley Research Center



CERES CRS

- CERES observes TOA radiation – but to understand climate we also need surface & atmospheric fluxes
 - The current L2 Single Scanner Footprint (SSF) product estimates surface fluxes w/ simple parameterizations (Model B)
- The Cloud Radiative Swath (CRS) product – reintroduced at last STM – builds upon the SSF by calculating instantaneous instrument footprint-level irradiances using the NASA LaRC Fu-Liou radiative transfer model
 - $SW_{\downarrow\uparrow}$ & $LW_{\downarrow\uparrow}$ broadband flux profiles + Surface narrowband SW & LW, direct + diffuse SW_{\downarrow} , PAR, UV fluxes
 - How does CRS compare to Surface-Only Flux Algorithms (SOFA) Model B & other CERES flux products?

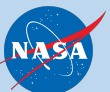


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- Here we update & extend our analysis from the last STM to cover an entire year (2019):

CRS vs (1) **CERES TOA observations**, (2) SSF Model B surface fluxes, (3) SYN1deg surface fluxes

	<i>CERES CRS</i>	CERES SSF Ed4A	FLASHFlux SSF v4A	CERES SYN1deg-Hr
L2 / L3	Instantaneous footprint	Instantaneous footprint	Instantaneous footprint	TISA gridded, hourly (L3)
Surface	Fu-Liou RT model	Model B parameterization	Model B parameterization	Fu-Liou RT model
TOA	Fu-Liou RT model	Observations	Observations	Fu-Liou & Observations

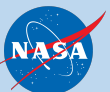


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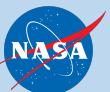


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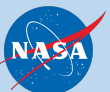
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- Can we use CRS to improve FLASHFlux low-latency surface fluxes for the applied science community?
 - (4) Preliminary development & evaluation of Machine Learning models to provide rapid & accurate surface radiative fluxes



Inputs

CERES SSF Ed4A
geolocated FOVs, etc.

GEOS 5.4.1
 $T(z)$, $p(z)$, $q(z)$, $O_3(z)$
surface wind speed

MODIS
cloud properties (Ed4)
AOD (sometimes)
spectral albedo
land temp (clear)

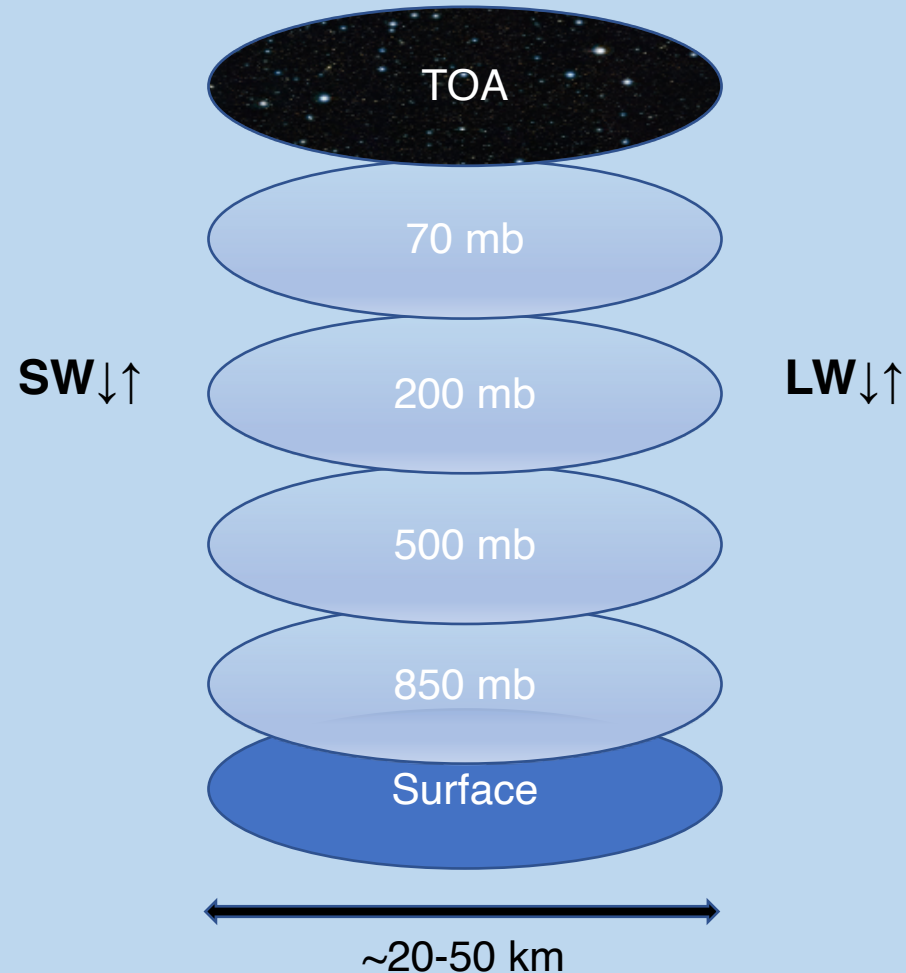
MATCH hourly
aerosol profiles & AOD

IGBP surface type

albedo history
map (cloudy)

CERES CRS

NASA Langley Fu-Liou
Radiative Transfer Model



CERES Footprint / FOV
Terra FM1, Aqua FM3

Outputs

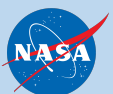
instantaneous vertical
profiles (6 levels) of
broadband flux &
spectrally-resolved fluxes
at the surface and TOA

LW : 12 bands
SW : 14 bands

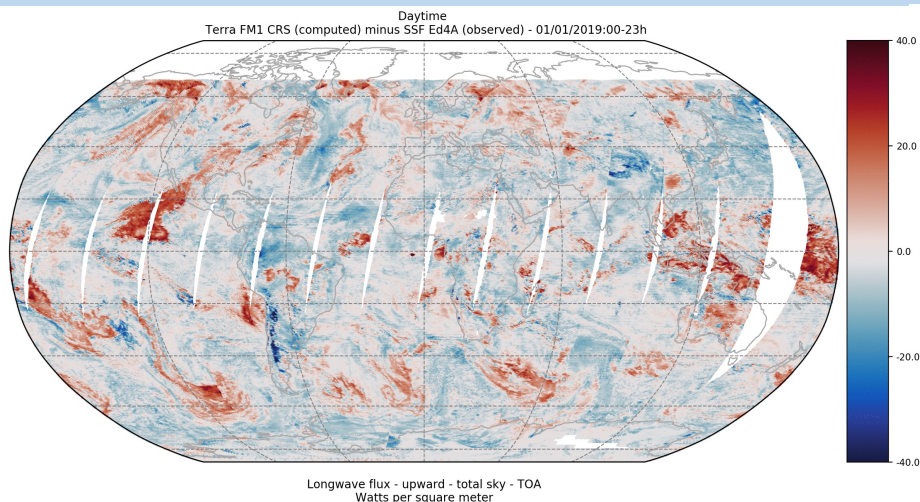
(surface, all-sky)
SW↓ direct + diffuse
PAR, UV fluxes

All-sky
Clear-sky
Pristine-sky
All-sky no aerosol

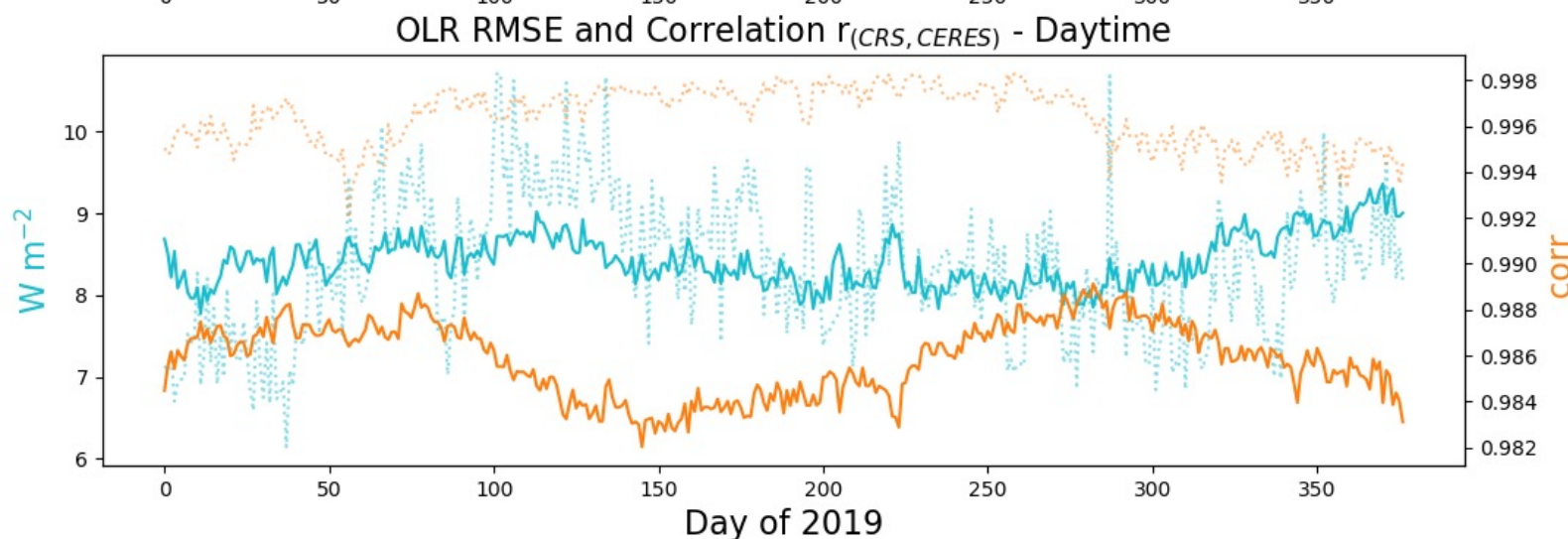
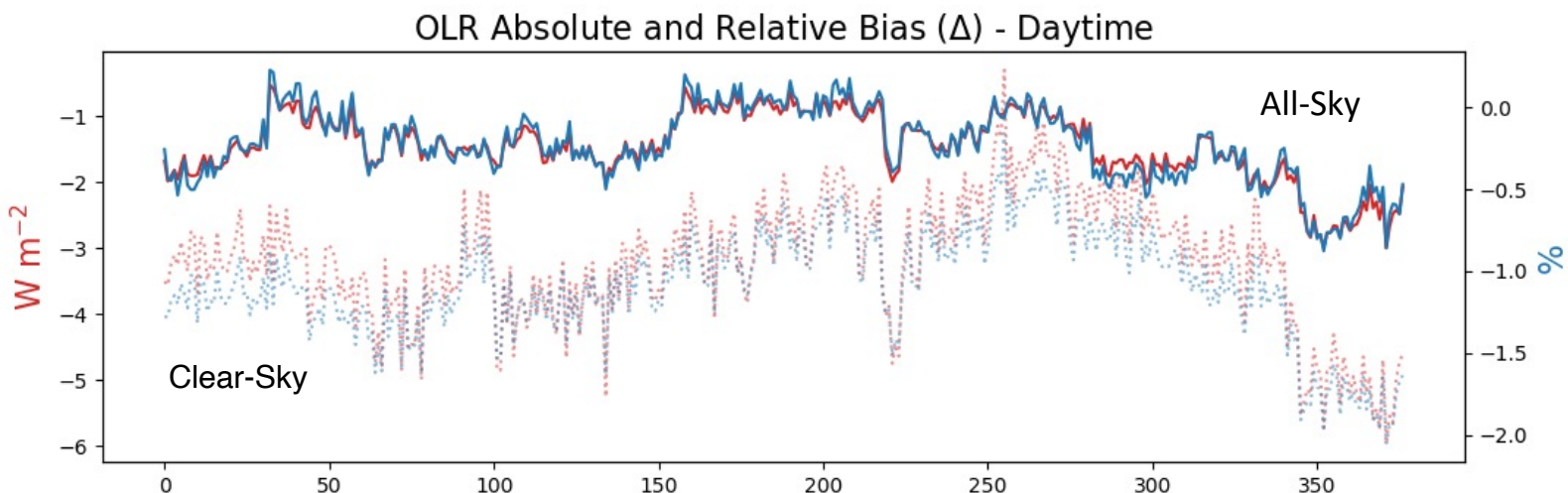
2-stream LW
4-stream SW



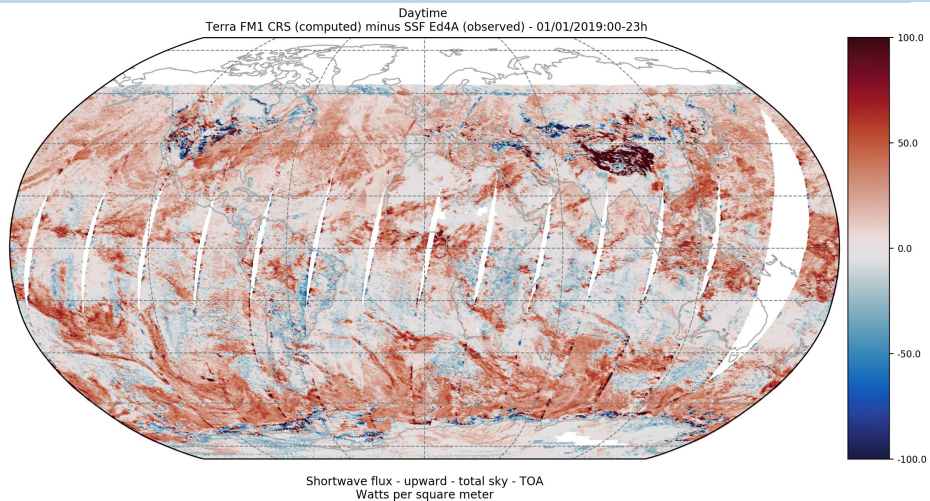
TOA CRS Computed LW↑ vs SSF Ed 4A Observations



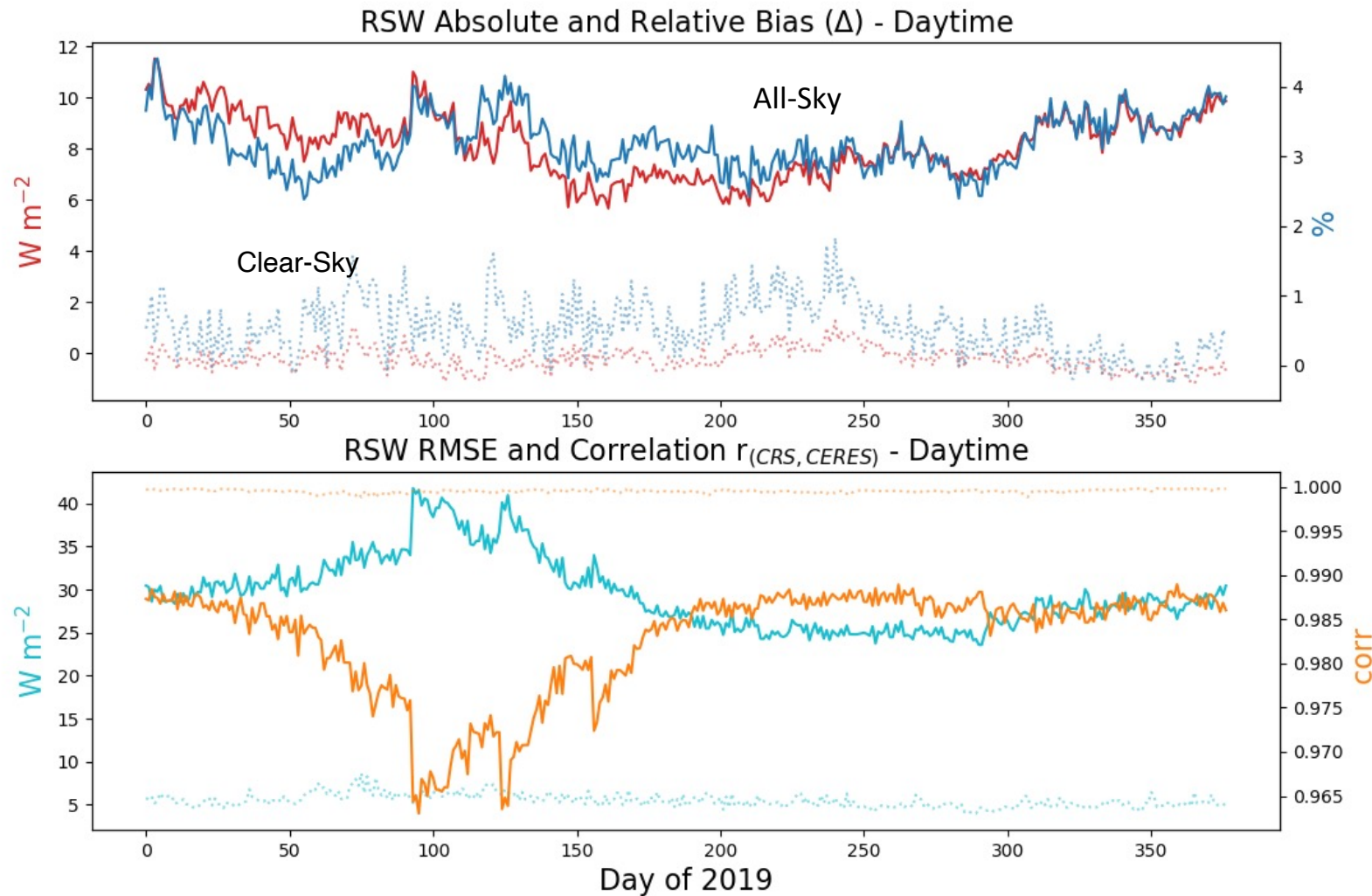
- (↑) Daily, geographic Δ OLR variability
 - CRS minus CERES SSF observations
- (→) Time series of OLR validation stats
- Global statistics remain relatively stable throughout 2019
- All-sky bias within -1% (~ -1 to -2 W m^{-2})
- Negative clear-sky bias compensated by excessive OLR from high clouds
- $\sim 7 \text{ W m}^{-2}$ global RMSE w/ strong correlation of modeled & observed fluxes



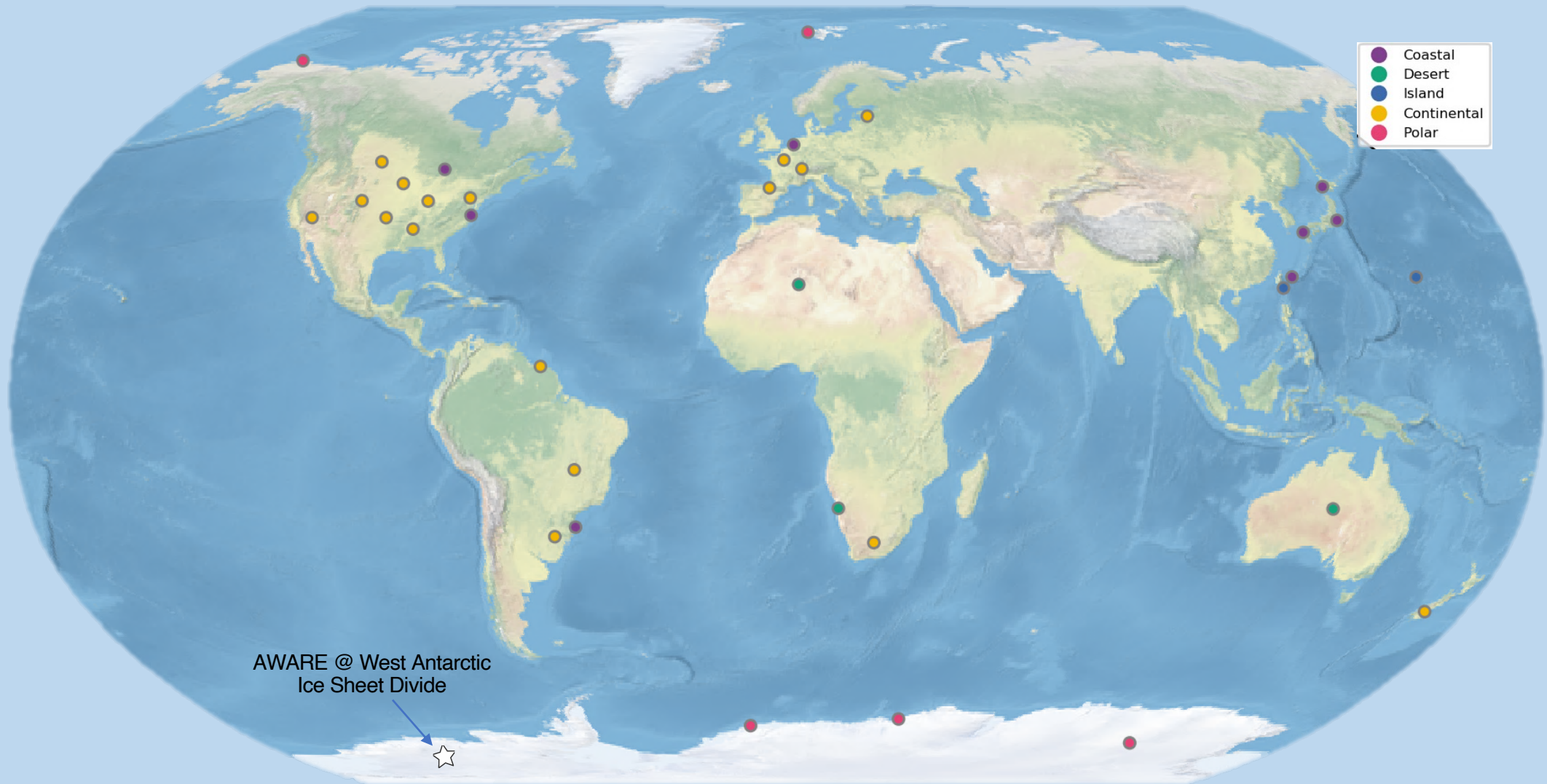
TOA CRS Computed SW \uparrow vs SSF Ed 4A Observations



- (\uparrow) Daily, geographic Δ RSW variability
 - CRS minus CERES SSF observations
- (\rightarrow) Time series of RSW validation stats
- Excessive reflection to space by clouds & occasionally the surface
 - $\sim 3 - 4\%$ global mean all-sky bias
- Better clear-sky performance
 - $\sim 0 - 1\%$ clear-sky relative bias
- Biases relatively stable through time
- RMS peak in boreal spring from surface albedo retrievals over NH continents

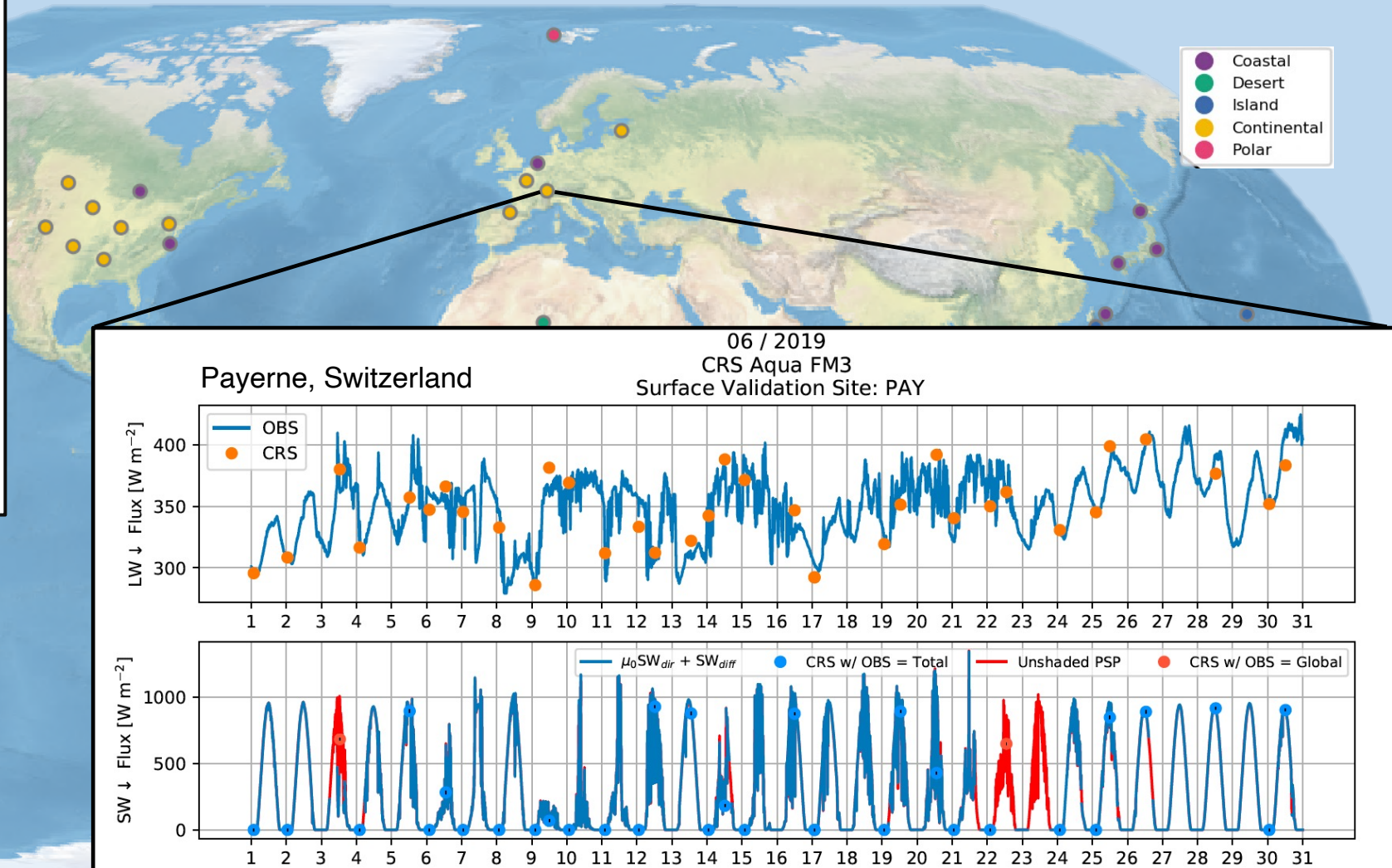


Surface Validation Sites

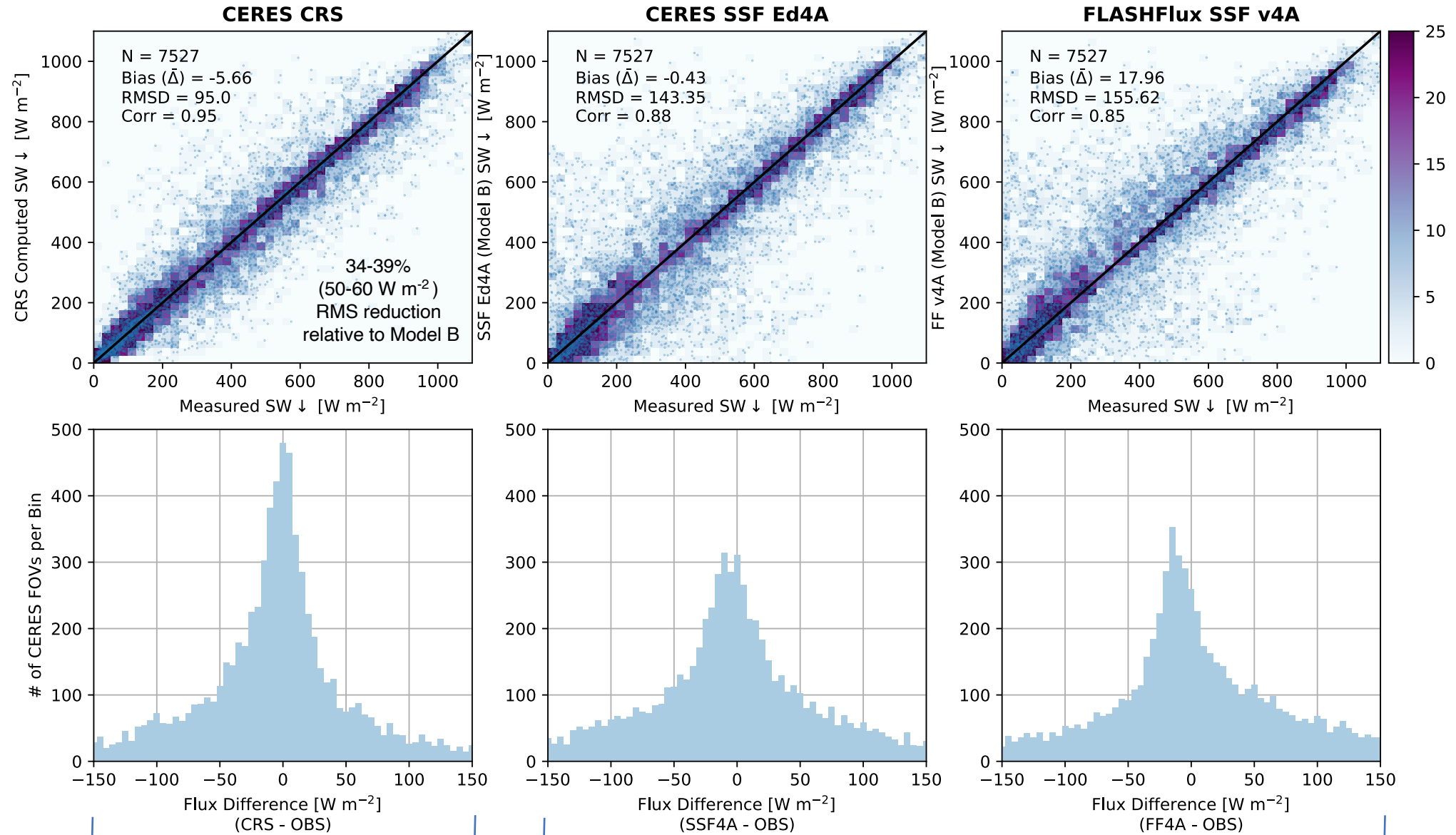


Surface Flux Validation Methodology

- Using 1-min resolution surface data
- Extracting footprints within 10 km
- **LW_↓** : instantaneous match to pyrgeometer obs. at footprint time
- **SW_↓** : averaging surface obs. for 30 mins centered at footprint time
 - **Total = Direct + Diffuse**, resort to **Global** from **unshaded PSP** if total is unavailable
 - **SW_{↓CRS}** scaled by $\text{avg}(\mu_{\text{OBS}}) / \mu_{\text{CRS}}$ to account for changing $\mu = \cos(\text{SZA})$
- FOV size varies with instrument view zenith angle (source of noise)

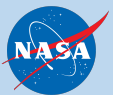


Surface Shortwave (SW ↓) Flux Validation Aqua FM3 - 2019 - Daytime Only - All Validation Sites



Fu-Liou RT Model Fluxes

Model B Parameterized Fluxes



Aqua FM3 Daytime SW↓ Fu-Liou vs Model B by surface type

CERES CRS

SW↓	N	Bias	RMSE	Corr.
All	7527	-5.66	<u>95.0</u>	<u>0.95</u>
Coastal	1366	<u>-4.4</u>	<u>100.21</u>	<u>0.93</u>
Desert	378	-11.4	<u>78.87</u>	<u>0.92</u>
Island	240	<u>45.62</u>	<u>147.13</u>	<u>0.86</u>
Continent	3049	<u>-1.69</u>	<u>108.32</u>	<u>0.92</u>
Polar	2494	<u>-15.27</u>	<u>66.11</u>	<u>0.94</u>

Fu-Liou RT Model Fluxes

CERES SSF Ed4A

SW↓	N	Bias	RMSE	Corr.
All	7527	<u>-0.43</u>	143.35	0.88
Coastal	1366	14.14	130.82	0.88
Desert	378	<u>-0.54</u>	89.09	0.89
Island	240	68.57	154.37	0.86
Continent	3049	6.12	120.36	0.91
Polar	2494	-23.03	177.32	0.58

Model B Parameterized Fluxes

FLASHFlux SSF v4A

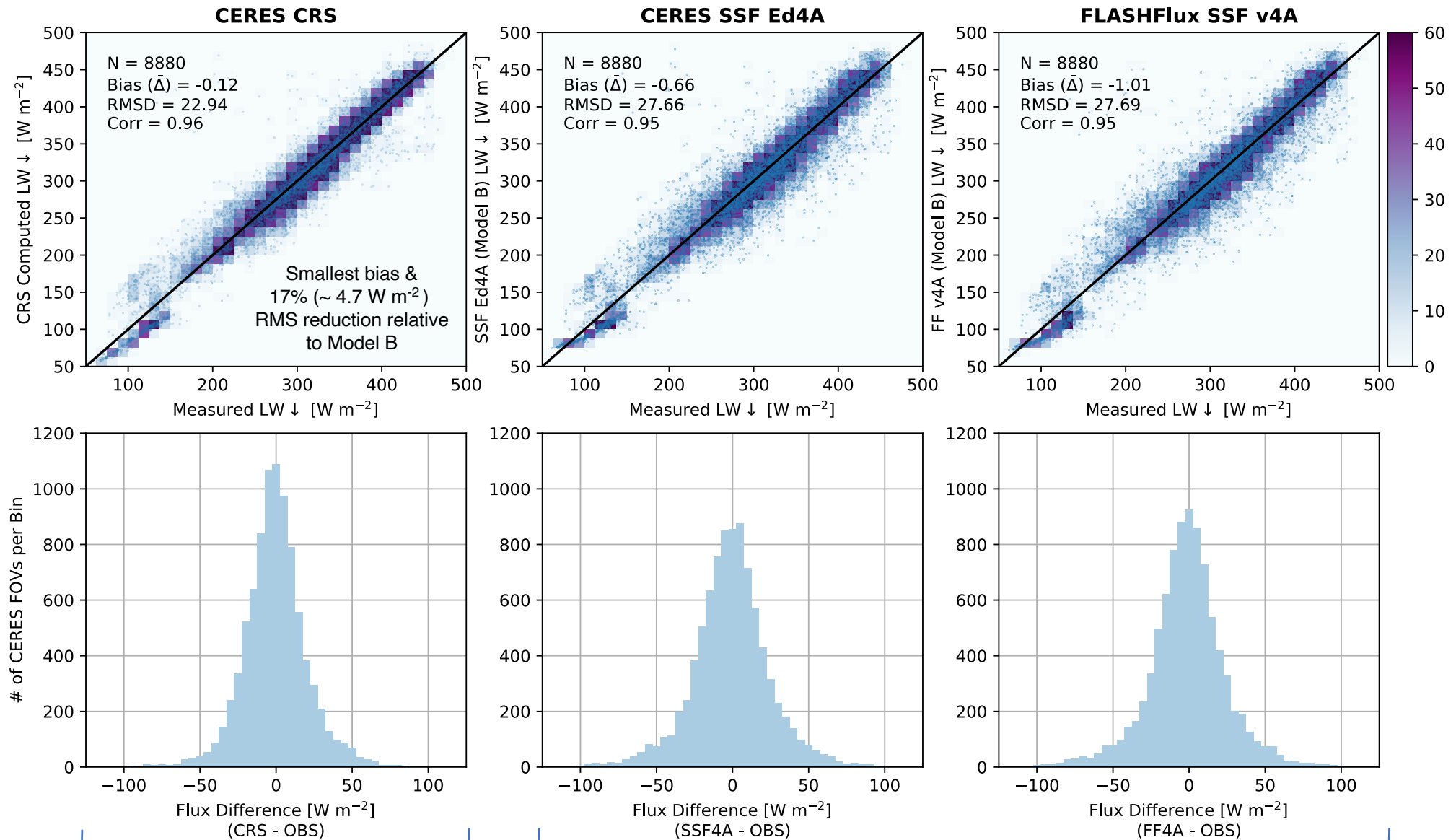
SW↓	N	Bias	RMSE	Corr.
All	7527	17.96	155.62	0.85
Coastal	1366	10.53	136.55	0.87
Desert	378	-13.7	92.74	0.88
Island	240	70.22	156.01	0.86
Continent	3049	13.39	132.54	0.88
Polar	2494	27.39	194.32	0.56

Results for Terra FM1 are similar

* Bias, RMSE units: W m⁻²

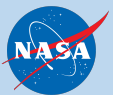


Surface Longwave (LW ↓) Flux Validation Aqua FM3 - 2019 - Daytime Only - All Validation Sites



Fu-Liou RT Model Fluxes

Model B Parameterized Fluxes



Aqua FM3 Daytime LW↓ Fu-Liou vs Model B by surface type

CERES CRS

LW↓	N	Bias	RMSE	Corr.
All	8880	<u>-0.12</u>	<u>22.94</u>	<u>0.96</u>
Coastal	1608	3.48	<u>15.56</u>	<u>0.97</u>
Desert	448	-13.04	<u>23.24</u>	<u>0.93</u>
Island	313	<u>4.98</u>	<u>13.72</u>	<u>0.87</u>
Continent	3293	3.56	<u>25.75</u>	<u>0.91</u>
Polar	3218	-4.37	<u>23.65</u>	<u>0.95</u>

Fu-Liou RT Model Fluxes

CERES SSF Ed4A

LW↓	N	Bias	RMSE	Corr.
All	8880	-0.66	27.66	0.95
Coastal	1608	<u>-0.38</u>	26.25	0.91
Desert	448	<u>-7.51</u>	29.71	0.85
Island	313	6.38	17.82	0.83
Continent	3293	0.9	28.73	0.89
Polar	3128	-2.13	27.73	0.93

Model B Parameterized Fluxes

FLASHFlux SSF v4A

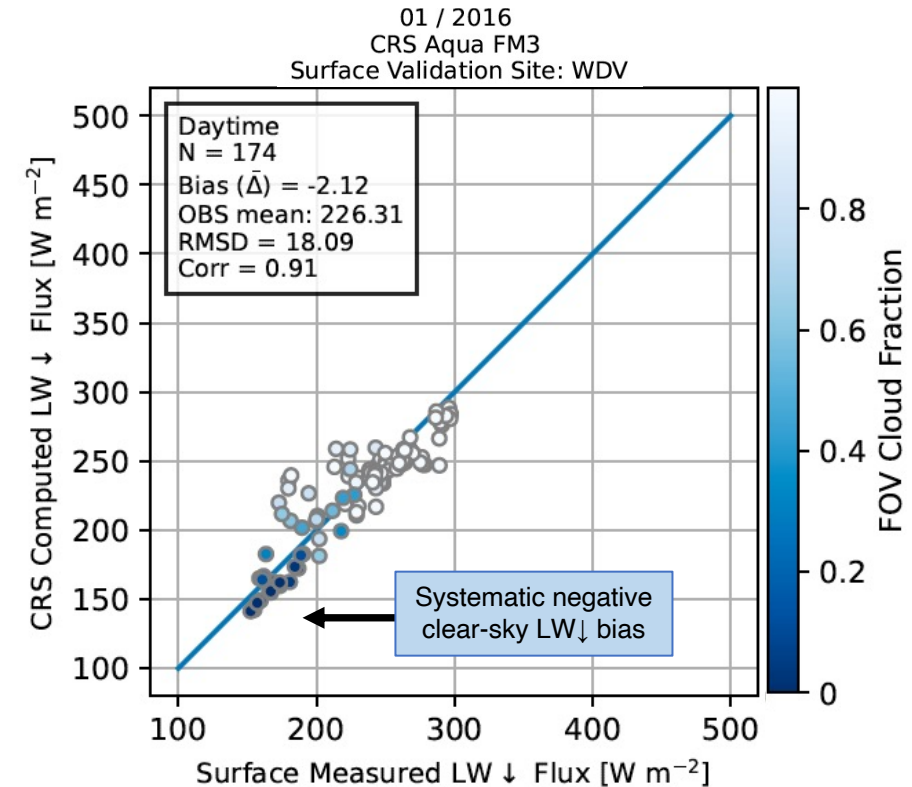
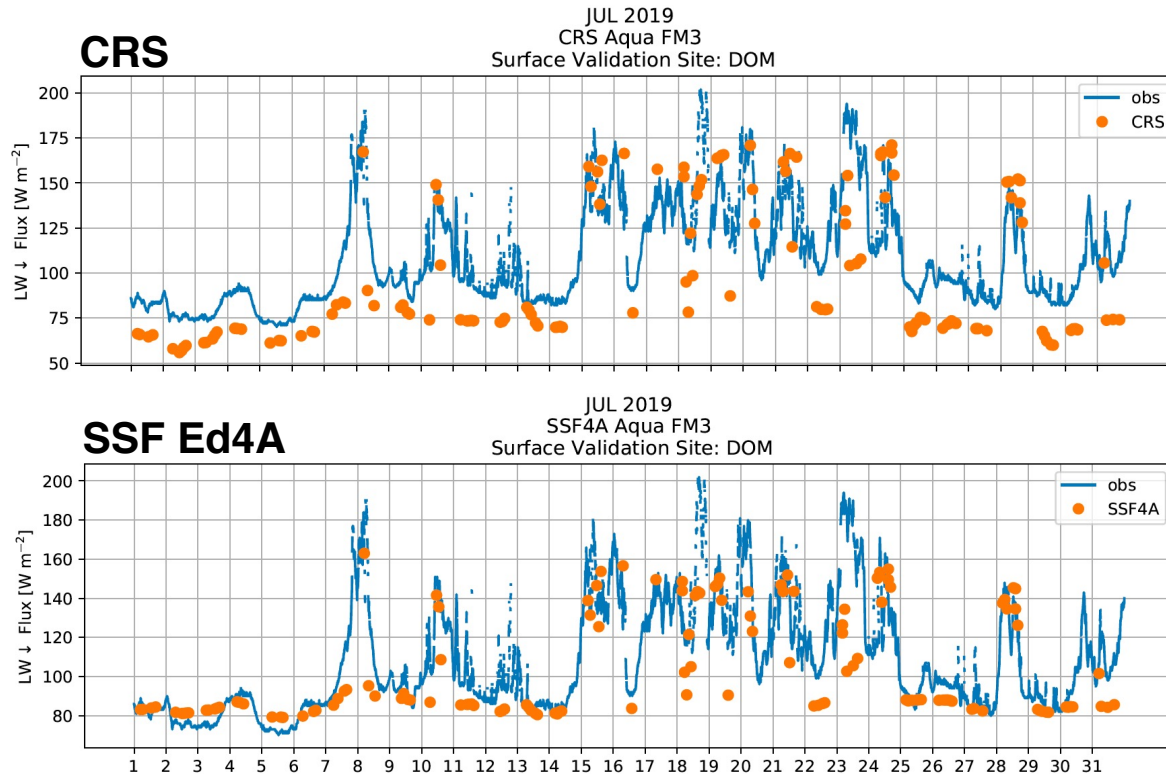
LW↓	N	Bias	RMSE	Corr.
All	8880	-1.01	27.69	0.95
Coastal	1608	-1.01	26.55	0.91
Desert	448	-7.83	26.78	0.87
Island	313	5.35	18.34	0.82
Continent	3293	<u>-0.7</u>	29.16	0.89
Polar	3128	<u>-1.0</u>	27.6	0.93

Results for Terra FM1 are similar

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Polar Clear-Sky Surface LW↓ Fluxes



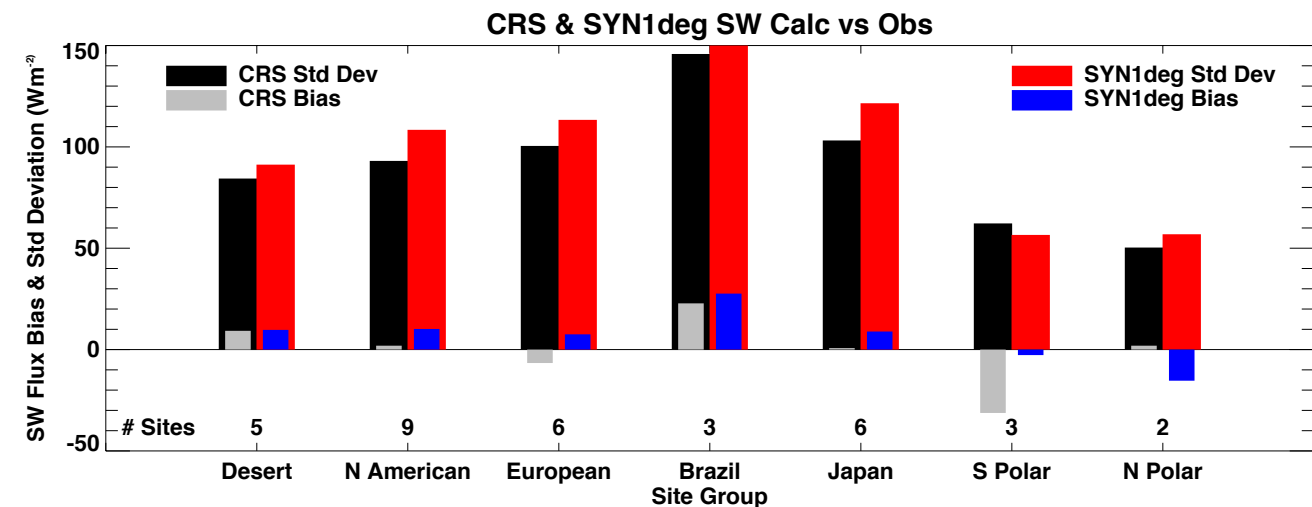
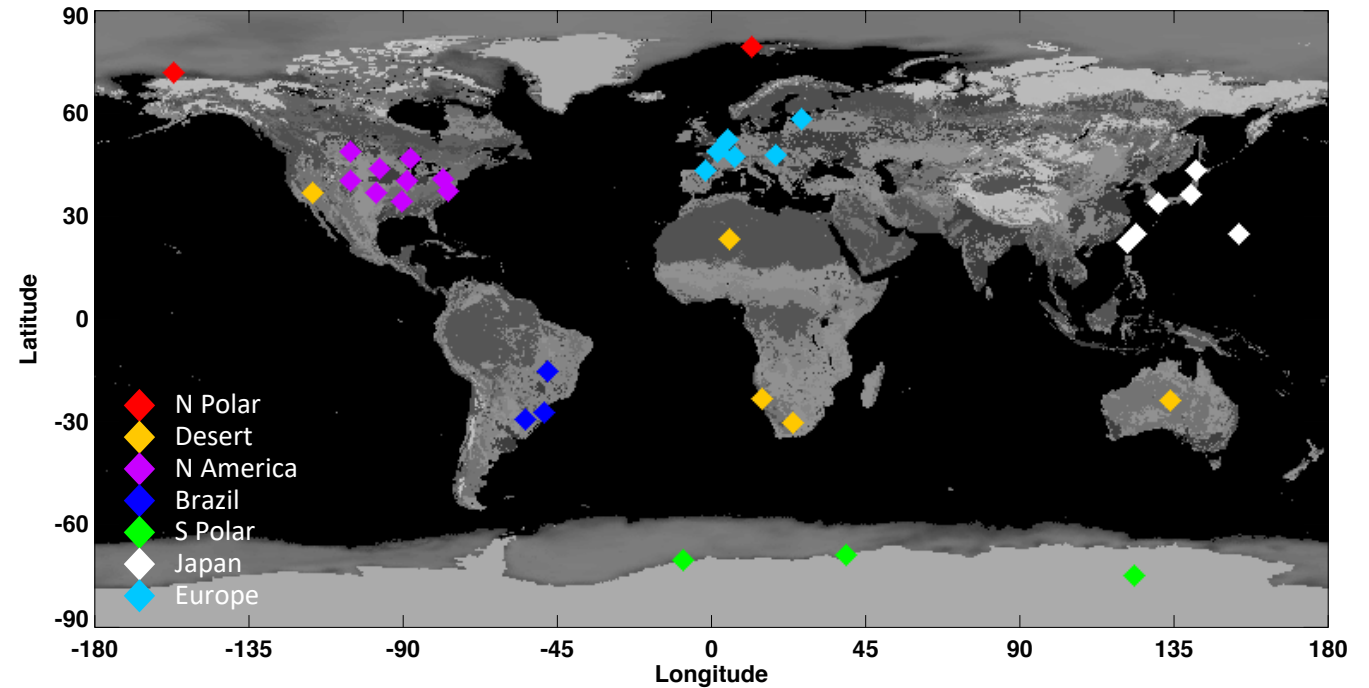
Systematic underestimation of clear-sky LW↓@ (left) **Dome C** & (right) **WAIS Divide, Antarctica**

Surface-based thermal inversion not well resolved in GEOS 5.4.1

Starting to develop inversion correction following Gupta et al. 2010

CRS vs SYN1deg Surface (\downarrow) Flux Validation

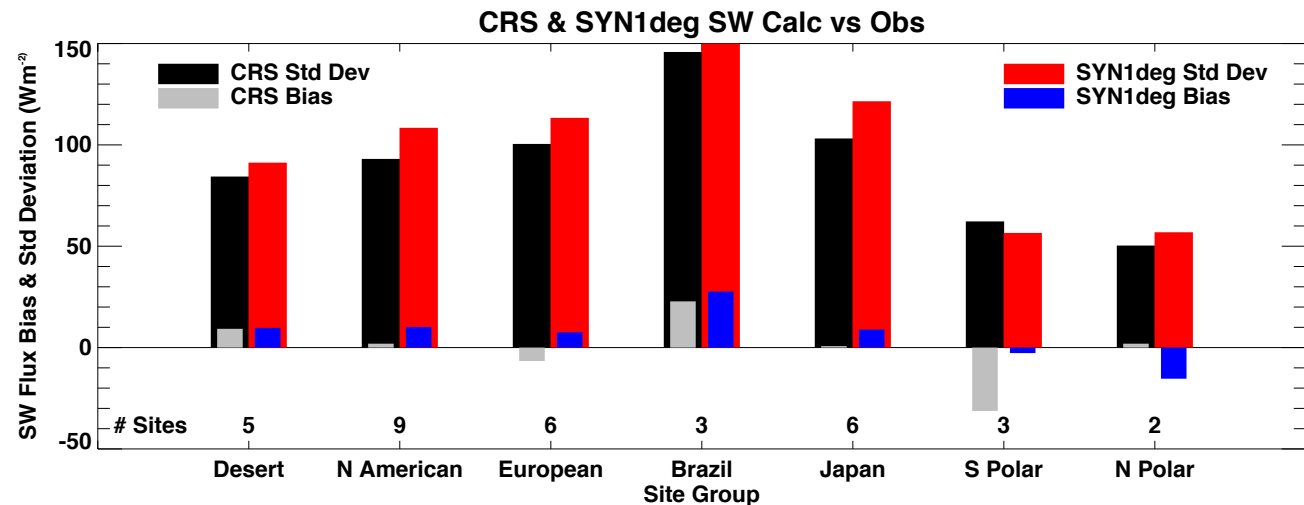
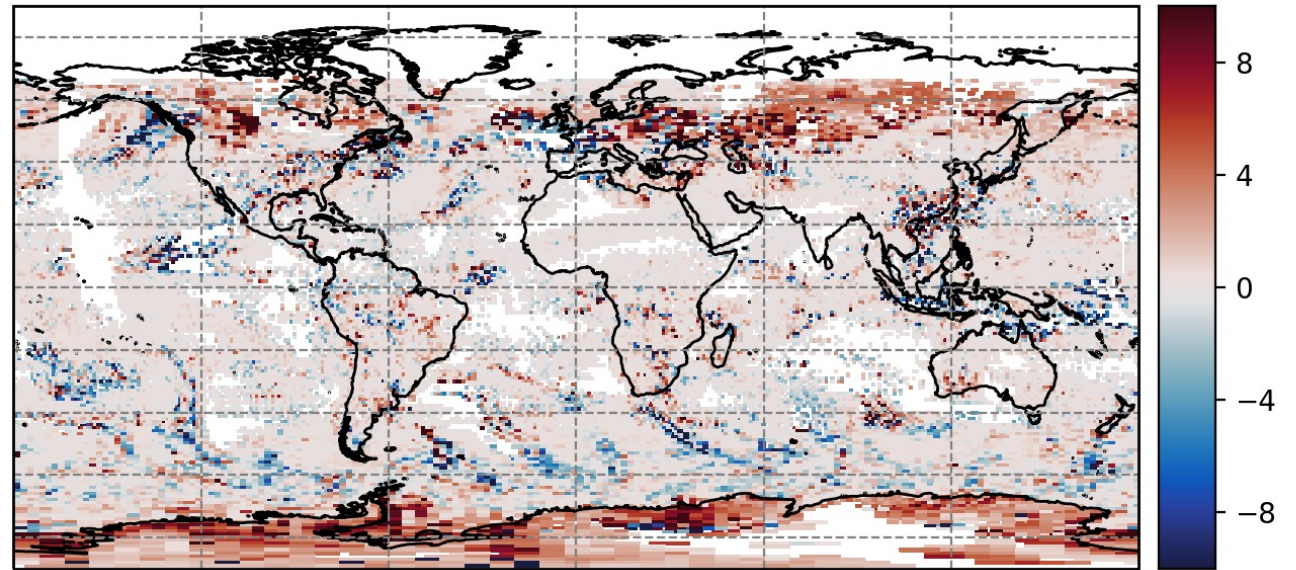
- SYN1deg provides gridded hourly surface fluxes also calculated using the Fu-Liou RT model
- We also compared CRS to SYN1deg
 - **SYN1deg** fluxes compared to **1-hr average** of the obs. centered on the half hour
- Both products are reasonably consistent & show similar statistics
- CRS has a smaller SW \downarrow bias & std. dev. (σ) everywhere but Antarctica
 - Footprints more representative of surface observations than 1° grid cells
 - CRS cloud optical depths are unrealistically high over permanent snow and ice surfaces
- CRS and SYN1deg also show similar results in the LW \downarrow



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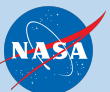
Daytime *Aqua Only* CRS1deg β -Hr minus SYN1deg-Hr
Cloud Optical Depth [no units] 01-01-2019:00-23h



Can We Use CRS & Machine Learning to Improve FLASHFlux SSF Surface Fluxes?

Problem:

- FLASHFlux (P. Stackhouse's talk next) provides near real-time estimates of Earth's surface radiation budget components for agricultural, renewable energy, and other applications
- Currently, footprint-level surface fluxes are estimated using decades-old parameterizations (Model B) that, as we just showed, are generally inferior to CRS fluxes from the Fu-Liou radiative transfer model.
- However, running the Fu-Liou code at the CERES instrument footprint level is computationally expensive (~ 2.3M computations, ~12-16+ hours/day) and increases the difficulty of meeting latency requirements



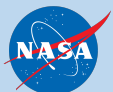
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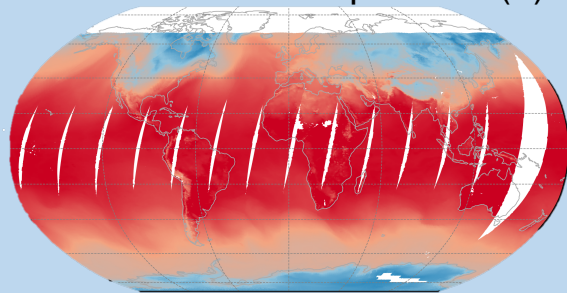
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Approach / Solution:

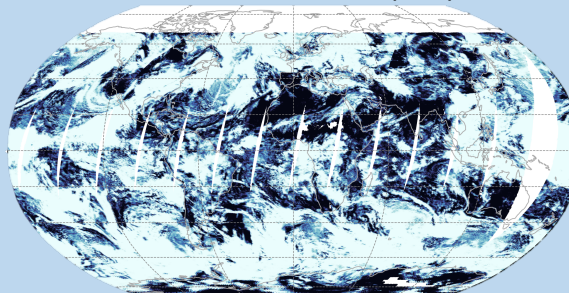
- Train supervised machine learning algorithms on CRS data, tune hyperparameters, & evaluate model performance to “learn” functional mappings that can *accurately* & *rapidly* predict CRS surface fluxes – no need to run the Fu-Liou RT code!
 - Linear, Decision Tree, Random Forest, & XGBoost Regressors



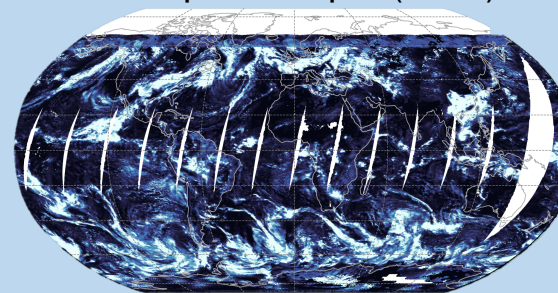
Eff. Emission Temperature (T)



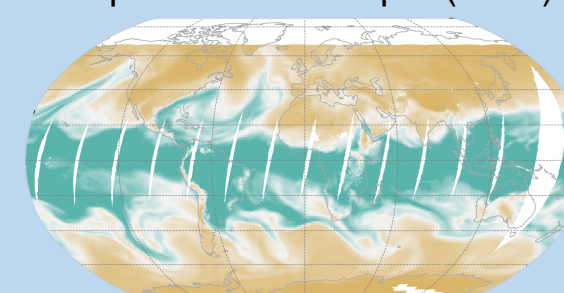
Cloud Fraction (CF)



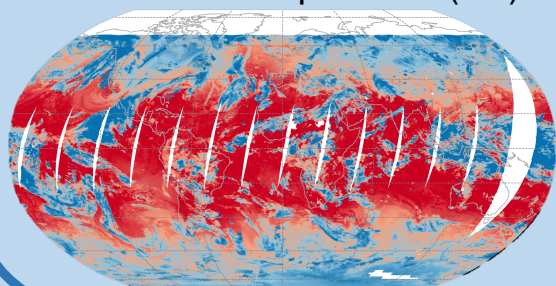
Cloud Optical Depth (COD)



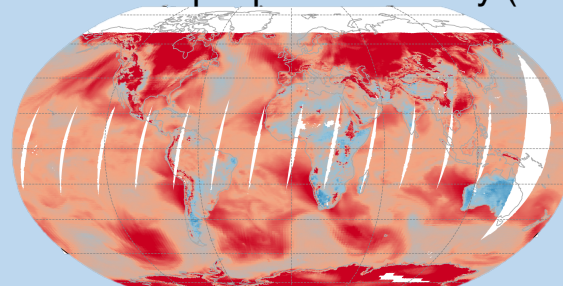
Precipitable Water Vapor (PWV)



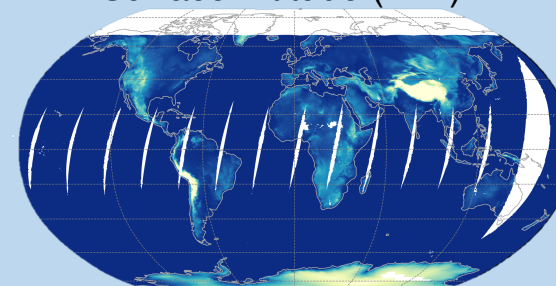
Eff. Cloud Temperature (CT)



Lower Tropospheric Stability (LTS)



Surface Altitude (ALT)



- Provides functional mappings between meteorological parameters

$\mathbf{X} =$

T, CF, COD, CT, PWV, LTS, ALT

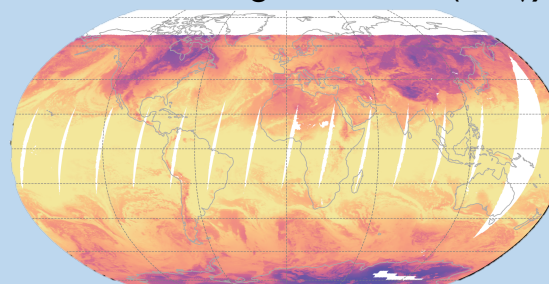
that are physically relevant and readily available in the FLASHFlux data processing stream & the CRS flux

$$\text{LW}\downarrow = f_i(\mathbf{X})$$

Supervised ML Algorithms:

Linear
Decision Tree
Random Forest
XGBoost

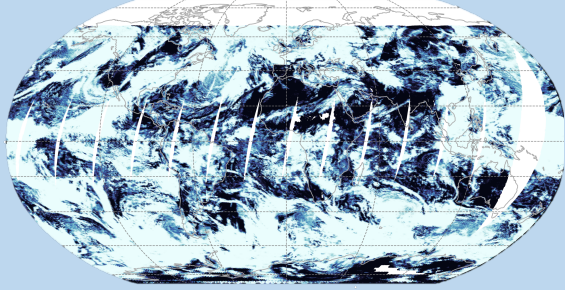
Surface Longwave Flux (LW↓)



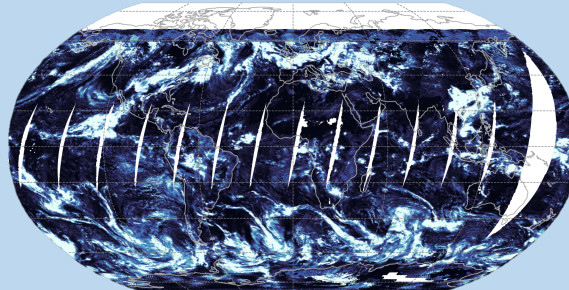
- Standardize X prior to training
- Train on day & night footprints
- Assess performance & tune hyperparameters using different evaluation metrics:

- 80/20 Train-Test Split
- K-Fold Cross Validation
- Randomized Search CV (in progress)

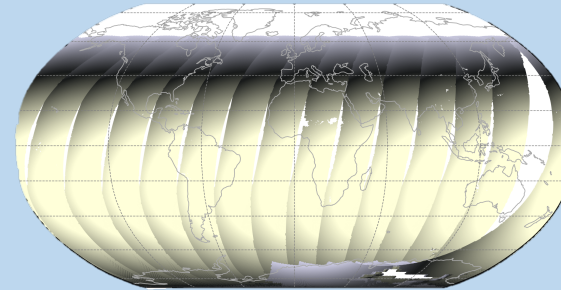
Cloud Fraction (CF)



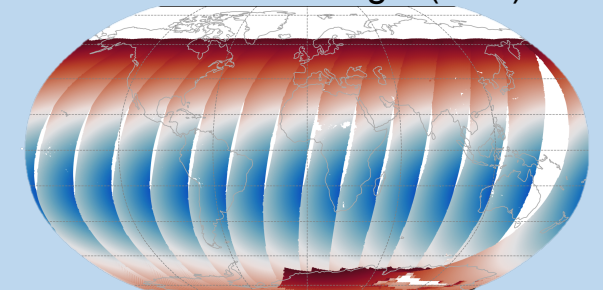
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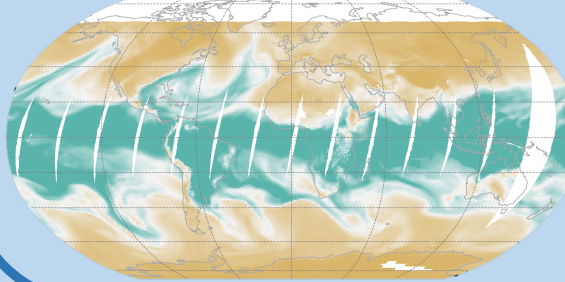
TOA Insolation (INS)



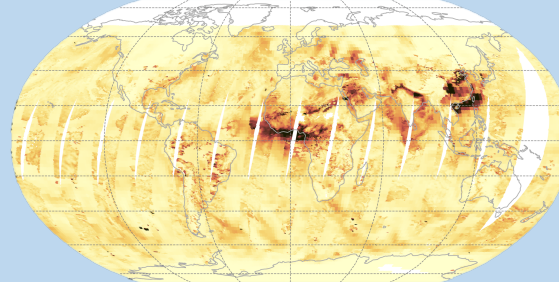
Solar Zenith Angle (SZA)



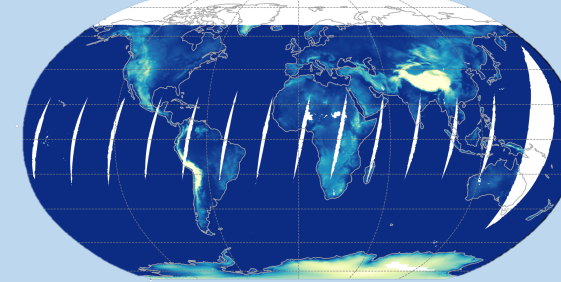
Precipitable Water Vapor (PWV)



Aerosol Optical Depth (AOD)



Surface Altitude (ALT)



- Provides functional mappings between meteorological parameters

$\mathbf{X} =$

INS, SZA, CF, COD, AOD, PWV, ALT

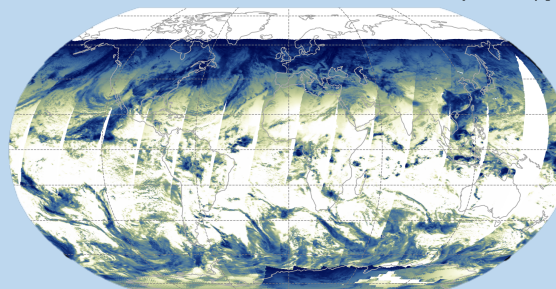
that are physically relevant and readily available in the FLASHFlux data processing stream & the CRS flux

$$SW\downarrow = g_i(\mathbf{X})$$

Supervised ML Algorithms:

Linear
Decision Tree
Random Forest
XGBoost

Surface Shortwave Flux ($SW\downarrow$)

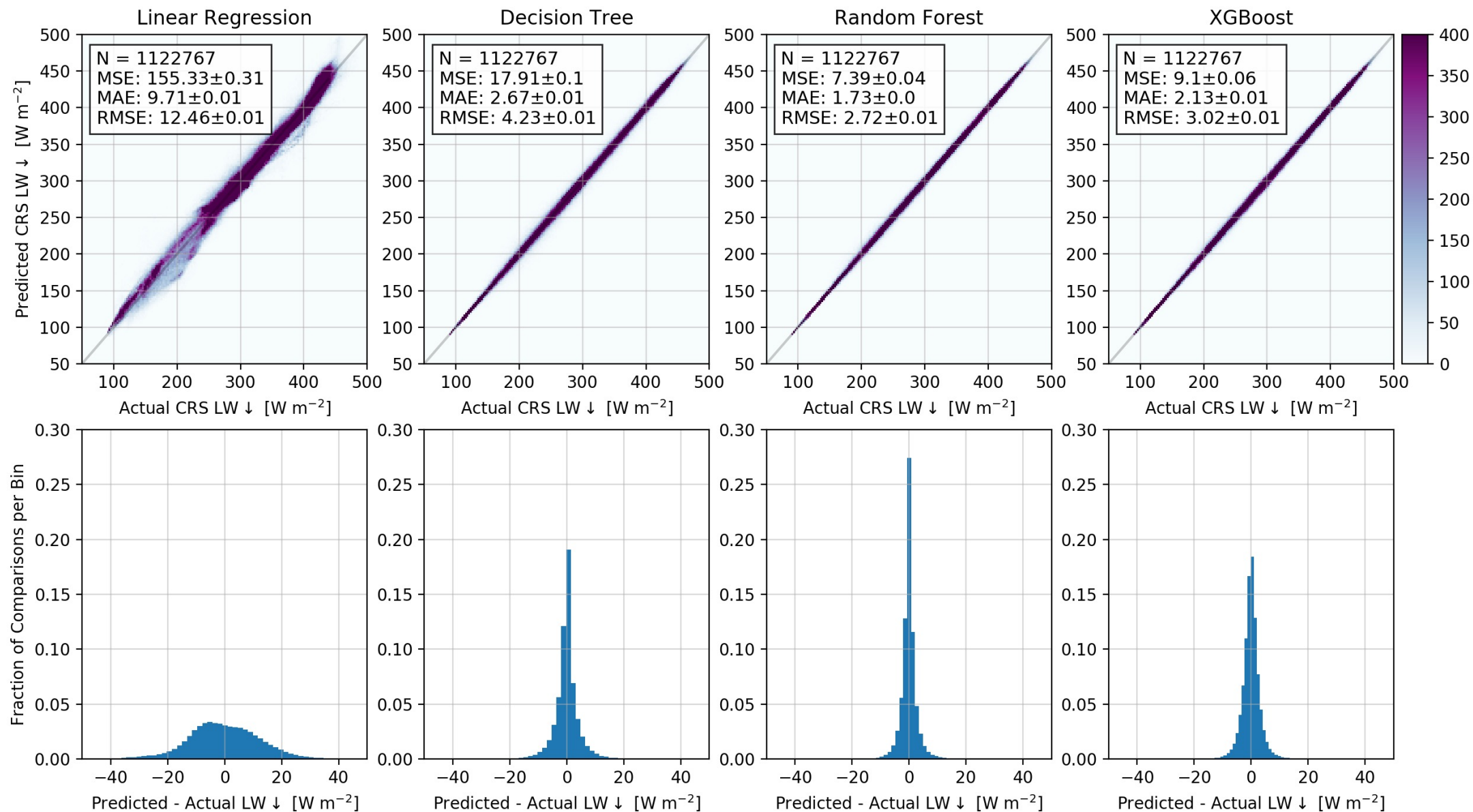


- Standardize \mathbf{X} prior to training
- Train on daytime footprints
- Assess performance & tune hyperparameters using different evaluation metrics:
 - 80/20 Train-Test Split
 - K-Fold Cross Validation
 - Randomized Search CV (in progress)

LW↓

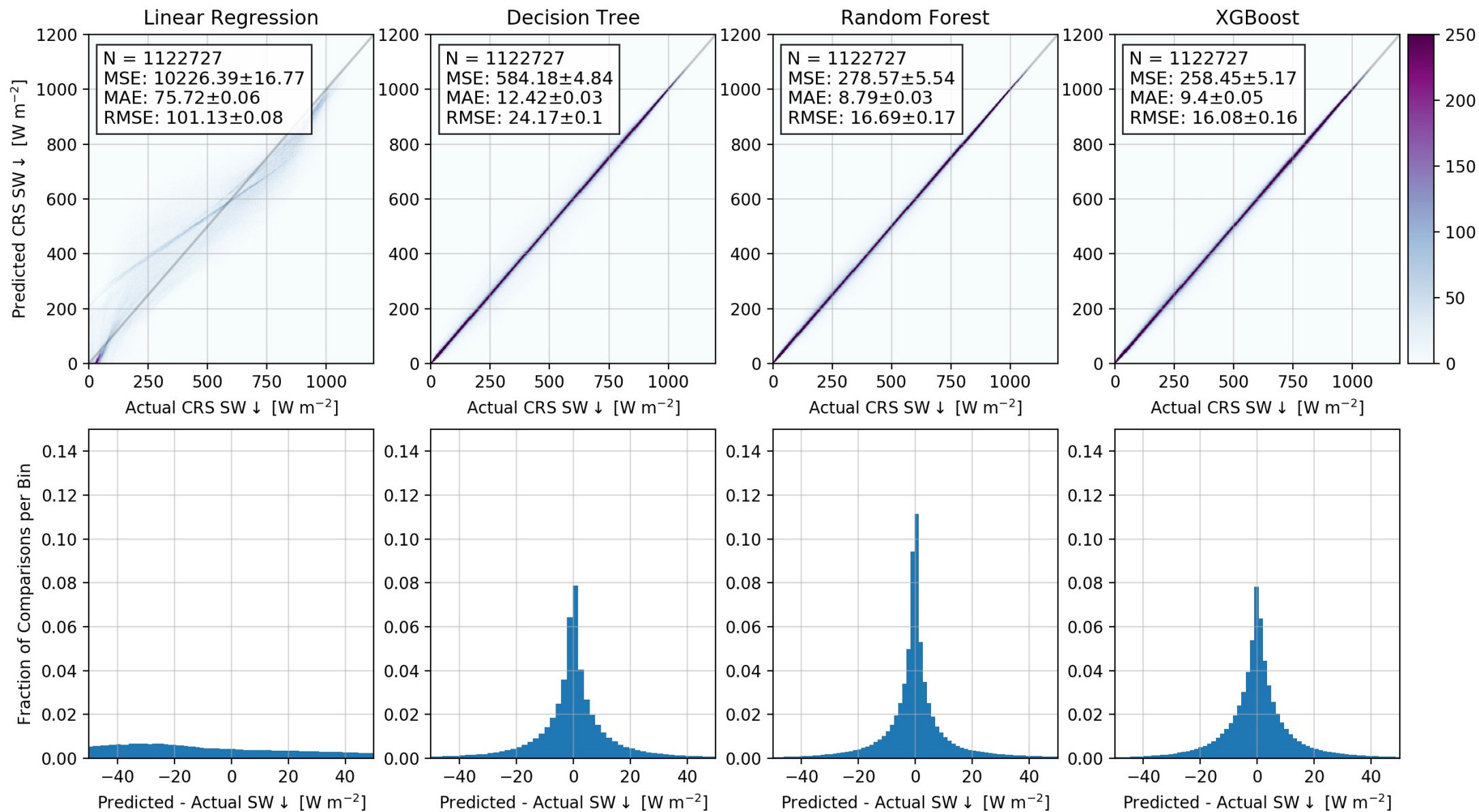
CER_CRS4_Terra-FM1-MODIS_GH4_1111TH.20190101:00-23h

Training features: Cloud properties (fraction, optical depth, temperature), \bar{T} , PWV, LTS, ALT



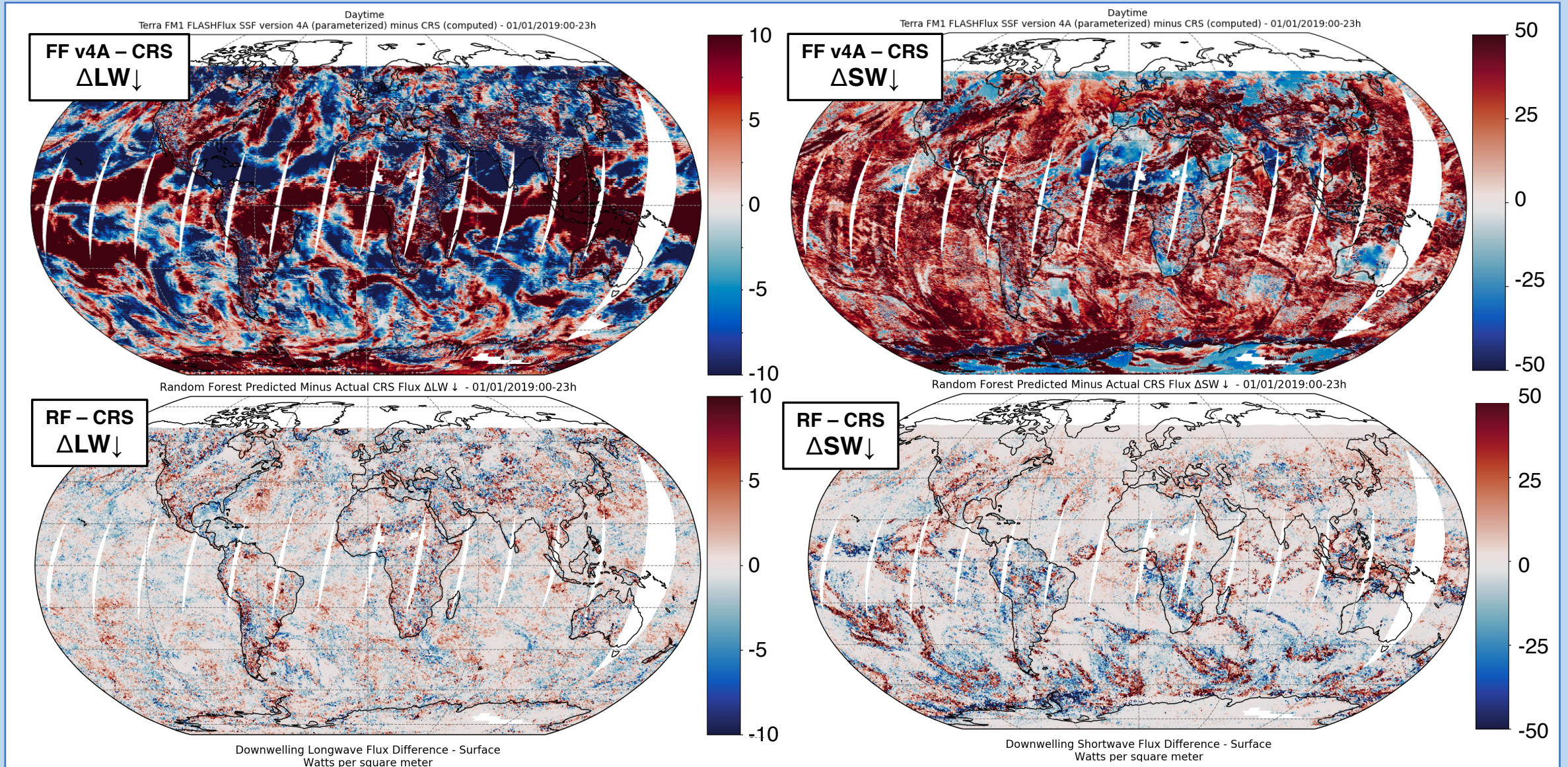
SW↓

CER_CRS4_Terra-FM1-MODIS_GH4_1111TH.20190101:00-23h
Training features: Insolation, \bar{SZA} , \bar{CF} , COD, AOD, PWV, Altitude



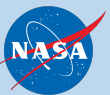
Random Forest (RF) surface flux predictions much closer to CRS than FLASHFlux Model B

(top) FLASHFlux SSF v4A – CRS (bottom) RF – CRS flux difference (Δ) [W m^{-2}]

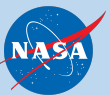


Summary & Future Work

- CRS computes instantaneous footprint-level irradiances using the NASA Langley Fu-Liou RT code
 - Here we summarized our progress resurrecting & validating CRS since we first reintroduced it 6 months ago
- Comparisons to CERES global TOA measurements show reasonable & stable performance
 - Global mean all-sky LW↑ within 1% of CERES, SW↑ within 3 - 4% of CERES throughout 2019
- CRS surface fluxes are superior to SOFA Model B parameterized fluxes (SSF Ed4A, FF SSF v4A)
 - Based on 2019 validation by surface site type using measurements from the CAVE database
 - SW↓ – RMS reduction of 34 - 39% (50 - 60 W m⁻²), higher correlation, lower bias for most site types
 - LW↓ – RMS reduction of 17% (~ 4.7 W m⁻²), marginally increased correlation, lowest overall bias
 - Corrections needed for excessive Antarctic cloud optical depth & unresolved temperature inversions
- Machine learning with CRS offers a viable solution to improve FLASHFlux SSF surface fluxes
 - We have developed, trained, & evaluated Linear, Decision Tree, Random Forest, & XGBoost regressors
 - Random Forest & XGBoost successfully reproduce CRS fluxes w/ model RMS values less than the validation RMS
Δ between CRS & Model B; individual footprint errors are typically << Δ(FF – CRS)
 - *Next Steps:* continue tuning models (RF & XGBoost) & devise scalable training methodology
deploy models in production & use as the operational source of FLASHFlux SSF surface fluxes
- We plan to release CRS publicly with CERES Edition 5 data products
- Thank You!



Extra Slides

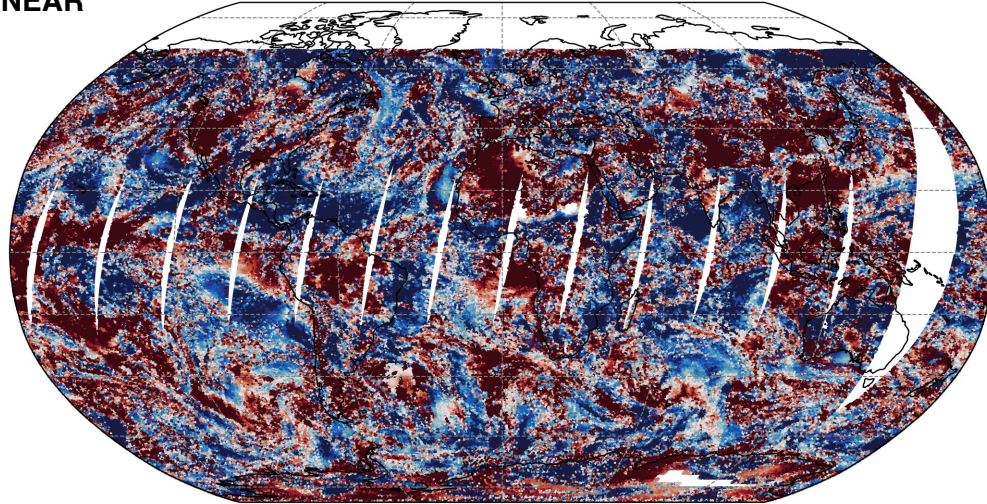


Surface LW↓ Model Performance

Predicted - Actual Flux [W m^{-2}]

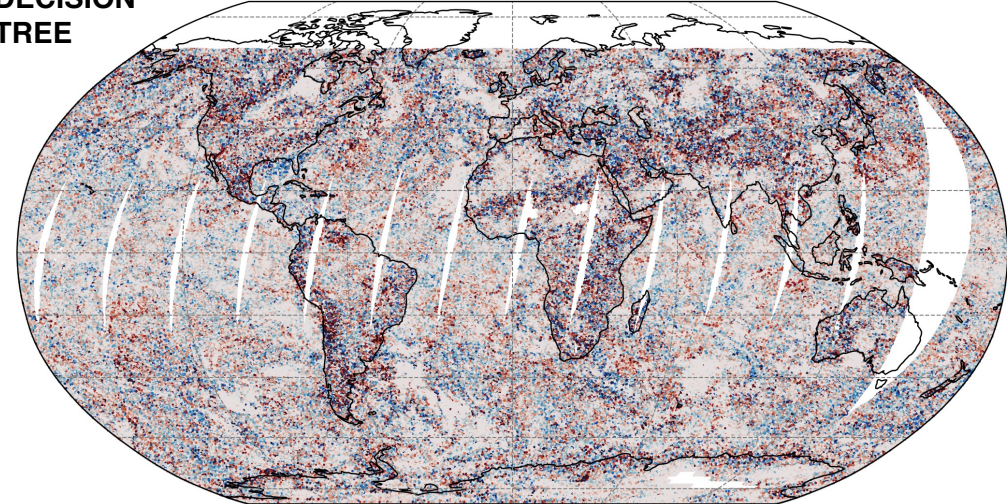
LINEAR

Linear Regression Predicted Minus Actual CRS Flux $\Delta\text{LW} \downarrow$ - 01/01/2019:00-23h



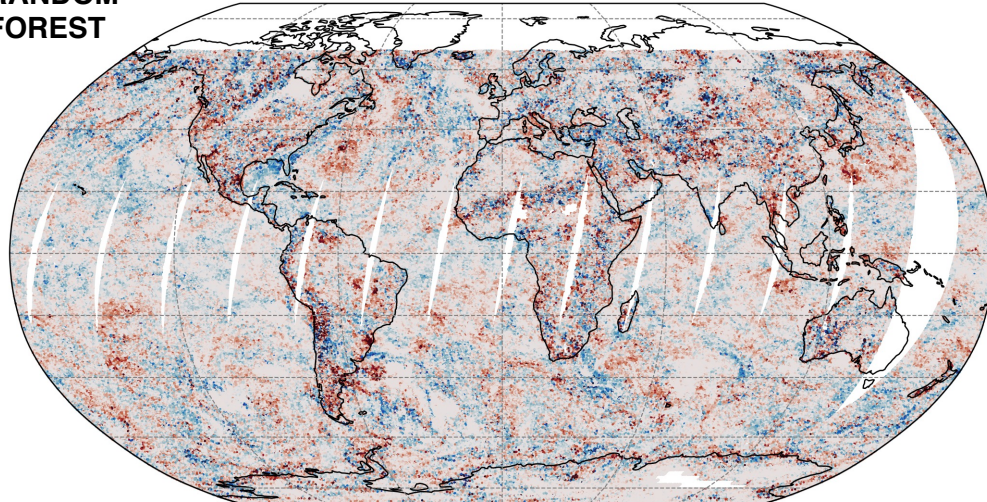
**DECISION
TREE**

Decision Tree Predicted Minus Actual CRS Flux $\Delta\text{LW} \downarrow$ - 01/01/2019:00-23h



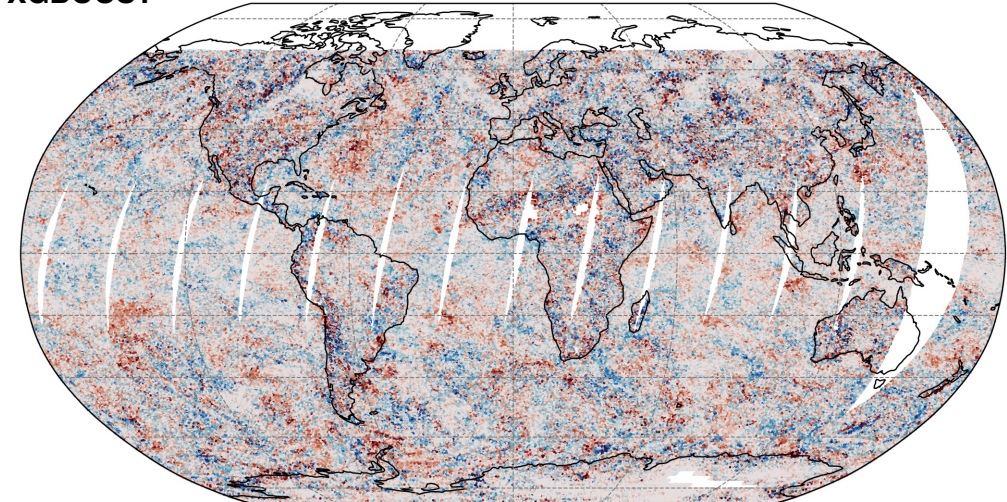
**RANDOM
FOREST**

Random Forest Predicted Minus Actual CRS Flux $\Delta\text{LW} \downarrow$ - 01/01/2019:00-23h



XGBOOST

XGBoost Predicted Minus Actual CRS Flux $\Delta\text{LW} \downarrow$ - 01/01/2019:00-23h



Downwelling Longwave Flux Difference - Surface
Watts per square meter

Downwelling Longwave Flux Difference - Surface
Watts per square meter

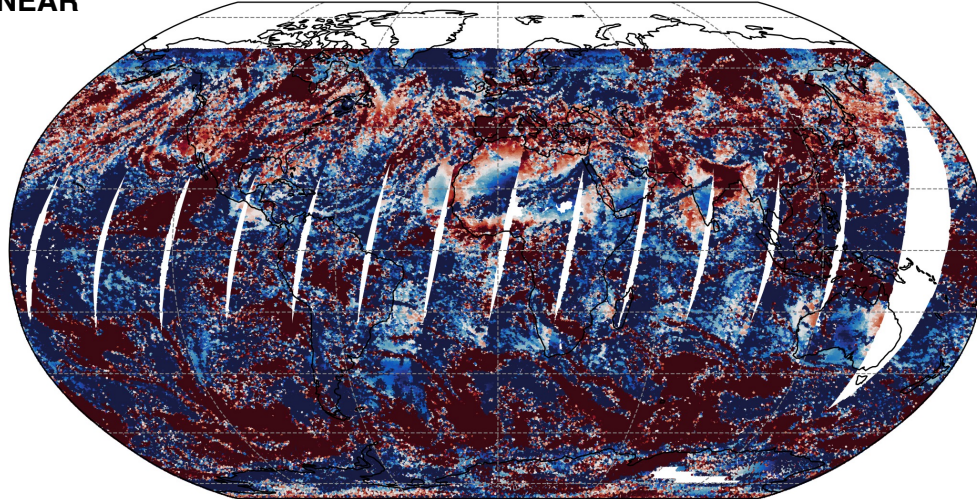


Surface SW↓ Model Performance

Predicted - Actual Flux [W m⁻²]

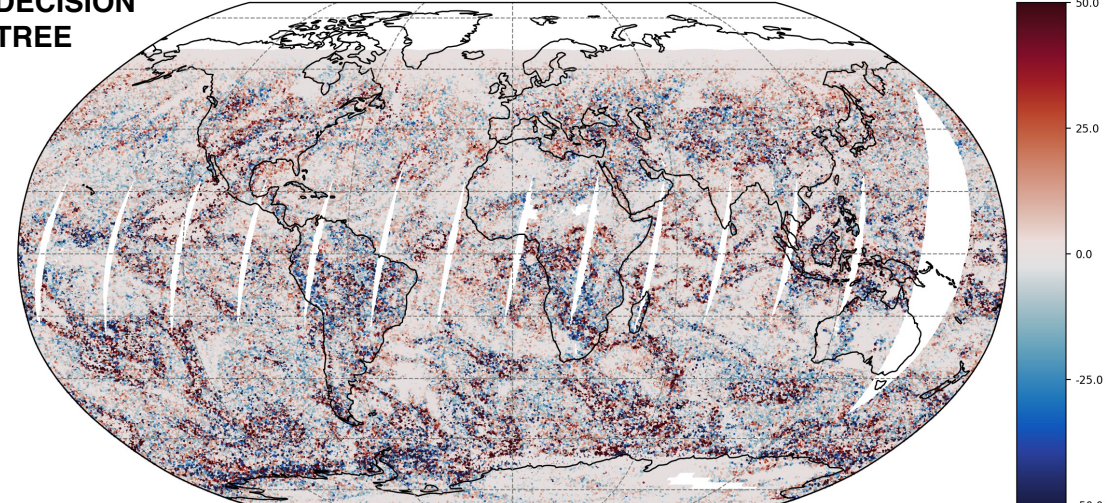
LINEAR

Linear Regression Predicted Minus Actual CRS Flux ΔSW ↓ - 01/01/2019:00-23h



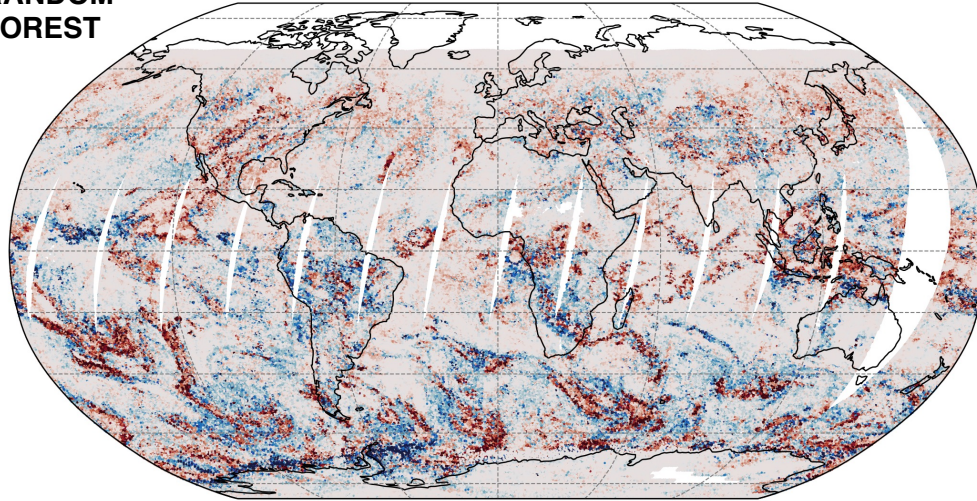
**DECISION
TREE**

Decision Tree Predicted Minus Actual CRS Flux ΔSW ↓ - 01/01/2019:00-23h



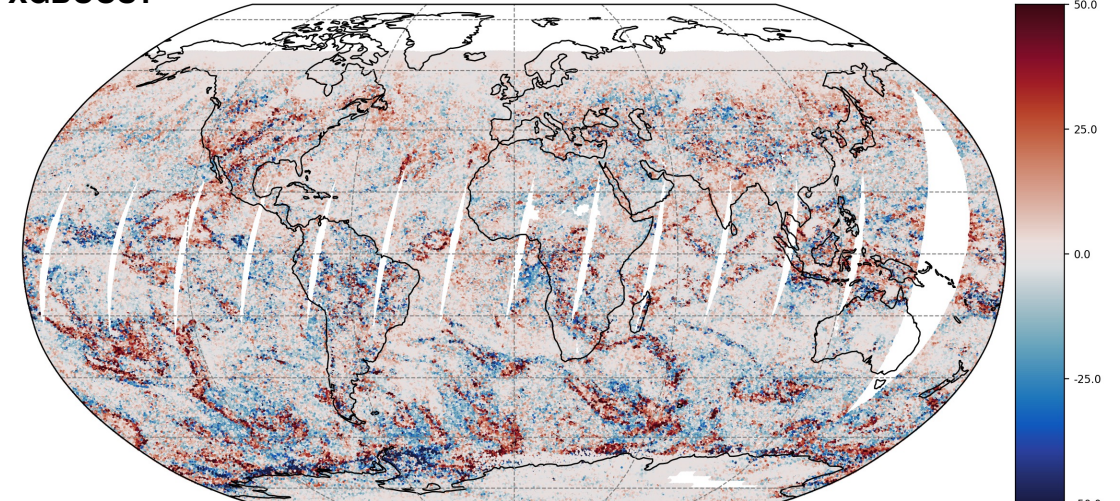
**RANDOM
FOREST**

Random Forest Predicted Minus Actual CRS Flux ΔSW ↓ - 01/01/2019:00-23h



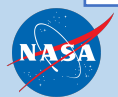
XGBOOST

XGBoost Predicted Minus Actual CRS Flux ΔSW ↓ - 01/01/2019:00-23h

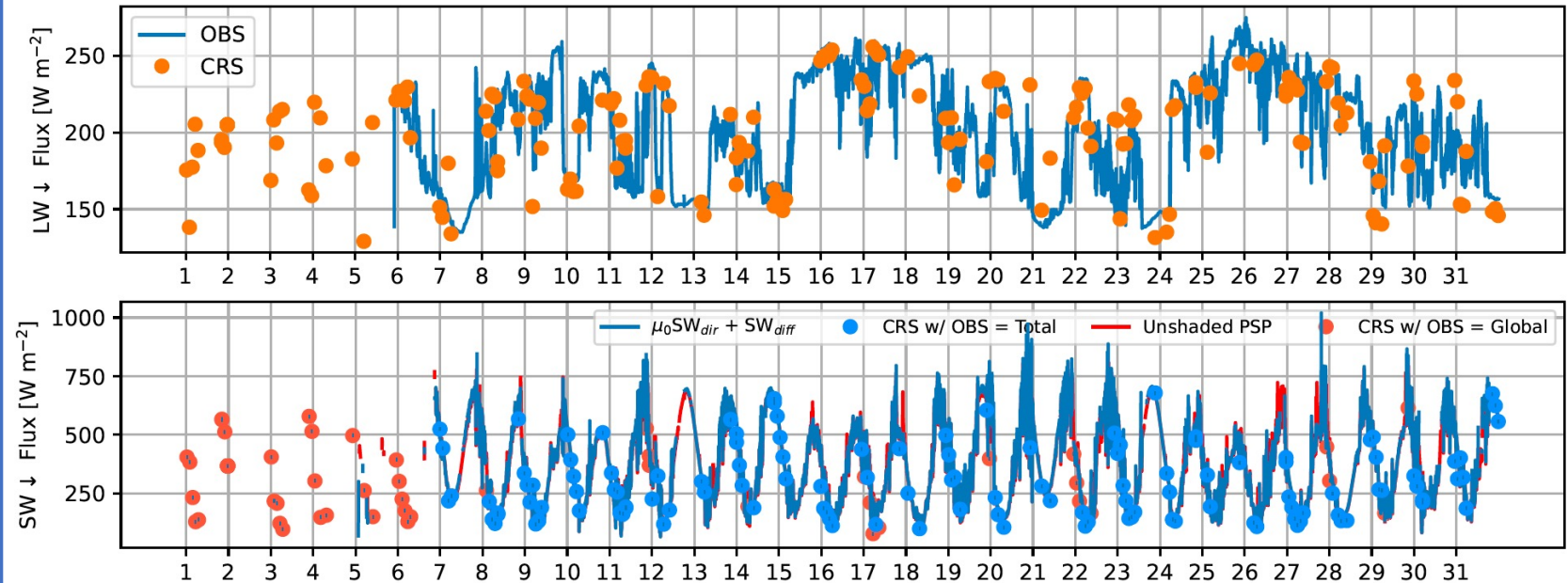


Downwelling Shortwave Flux Difference - Surface
Watts per square meter

Downwelling Shortwave Flux Difference - Surface
Watts per square meter



12 / 2015
CRS Aqua FM3
Surface Validation Site: WDV



ARM West Antarctic Radiation Experiment (AWARE) WAIS Divide, Antarctica

